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14. ABSTRACT
Many areas of military concern, such as command and control of forces, operations on urban terrain, and humanitarian assistance/disaster relief operations, are replete with human interactions. The complexity of these operations along with the confluence of possible interactions outside of the control of the local commander creates situations that are not easily modeled. Increasingly these multifaceted operations are being studied using agent-based models (ABMs).

While ABMs have been around for some time, those used in the military have been warfighting models. The agents possess weapons, abilities to sense, communicate, and move, and different allegiances. However, they do not have the abilities to carry, consume, or transfer resources. We describe the minimal core of capability for ABMs to successfully support logistics operations: defining a commodity, attaching it to an agent, transferring it between agents, and defining appropriate measures.

Logistics functions are extremely important for the U.S. Armed Forces, and logisticians must be prepared to take the lead in drafting operational plans. The ability to quickly put together ABMs and explore their behavior over a wide range of parameter settings might help support logistics operations. We illustrate the process for logistics support model in an urban, humanitarian assistance/disaster relief scenario.

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USING AGENTS TO MODEL LOGISTICS

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INTRODUCTION

The validity and usefulness of agent-based models (ABMs) remains an ongoing contention within the analysis community. The U.S. Marine Corps, through the proponency of Project Albert, is one of the leading agencies working to address this area of research. Specifically, Project Albert is interested in exploring ways of sorting through the huge sample spaces generated by an agent-based approach to gain insight into real-life, operational problems (Horne 2002). To date, Project Albert has ushered the development of several ABM environments. These environments have been used to generate abstract models of real-world problems. Because of the decidedly sparse, and thereby rapid, approach to modeling, Project Albert calls the abstracts *distillations* or *agent-based distillations.*

Concurrently, Project Albert has introduced the idea of *data farming*. Data farming is an iterative technique that resamples areas of the data space the analyst wants to research more closely. This resampling can be conducted quickly because Project Albert uses supercomputers to execute thousands of model runs in a relatively short amount of time. Furthermore, the setup and feedback of the data farming runs can be done over the internet through a simple interface. Project Albert has put together a complete package, including a set of ABMs, an easy-to-use data farming process, and visualization tools, to facilitate the exploration of military operations.

Project Albert currently utilizes four ABM environments. These are ISAAC: *Irreducible Semi-Autonomous Adaptive Combat* (Ilachinski 1997), MANA: *Map Aware Non-uniform Automata* (Stephen et al. 2002), Socrates (L-3 Communications Analytics Corp. 2003) and Pythagoras (Northrop Grumman Corp. 2003). Each of these platforms is built on a different set of assumptions and logic for controlling agent behavior, so the choice of platforms depends in large part on the type of questions the analyst is asking. Scenarios built in any of these environments can be run on supercomputing clusters at the Maui High Performance Computing Center in Maui, Hawaii or the Gilgamesh cluster at MITRE Corporation in Woodbridge, Virginia. The end goal is to support real-time decision-making. The suite of ABM platforms, together with an easy-to-use environment for data farming and visualization tools for displaying the output, facilitate the development and exploration of agent-based scenarios. Further information about Project Albert can be found in its publications (Horne and Leonardi 2000, Horne and Johnson 2002-3) or at the U.S. Marine Corps Warfighting Laboratory's website (MCWL 2003).

The structure was thus in place for rapid model development and exploration, but the modeling platforms had been developed primarily to examine the human dimension of combat. Our goal was to determine how agent-based platforms and the data-farming environment could be used to model logistics support with a focus on humanitarian assistance/disaster relief (HA/DR) operations.

In this paper, we begin with a brief description of how we use the term *agent* and our motivation for using ABMs to explore logistics support to HA/DR operations. We present a prototypical HA/DR scenario to illustrate agent attributes and motivate further discussion. We then propose what we feel are the minimal requirements that should be incorporated into ABMs to render them useful for creating distillations of logistics operations. We provide an example of creatively using existing model capabilities to mimic some of these aspects in our HA/DR scenario and give a brief summary of the insights gained from data-farming this scenario. We also describe alternative approaches for incorporating logistics in some of the other ABM platforms, and conclude with a summary of the importance of this approach and possibilities for the future.

MILITARY AGENT-BASED MODELS

Many areas of military concern, such as command and control of forces, operations in urban terrain, and HA/DR operations, are replete with human interactions. The complexity of these operations along with the confluence of possible interactions outside of the control of the local commander creates a situation that is not easily modeled. Increasingly these multifaceted operations are being studied using ABMs.

ABMs provide an environment in which entities, controlled by decision-making algorithms, can maneuver. These entities, known as agents, execute many local interactions resulting in the emergence of global behaviors. The agents are autonomous individuals or groups that often interact in a self-adaptive, non-linear manner with each time step. This self-adaptive behavior creates a vast number of variables, and facilitates research into emergent behaviors. The aggregate effects of the myriad of individual decisions can be studied, for a given scenario, in order to assess the effects on the whole system. These systems, including the agents, the environment they maneuver in, and the rule-set by which they make decisions, are known as *complex adaptive systems* (Stephen et al. 2002).

Agents may possess three types of characteristics: general, physical, and personality. General characteristics are specified at the outset of a run and do not change throughout the run. We can think of these as representing the core essence of the agent, such as the type of agent (soldier, helicopter, truck, or biological agent), the agent's squad, movement algorithms, and set of potential waypoints. These, in turn, may dictate fuel or carrying capacities, specify movement algorithms and limitations, or identify other agents with whom information can be shared. Physical characteristics can include weapons, with specified firing ranges, lethality, and accuracy. Sensing and communication characteristics may represent anything from sight and hearing to high-tech devices. Physical characteristics can also be sensitive to (i.e., depend on) terrain, enemy presence and state changes within a run. Finally, personality characteristics propel an agent toward or away from friends, enemies, waypoints or terrain features. They indicate an agent's desired response when encountering one of these elements within a run. Furthermore, that response can also be sensitive to state changes in the scenario. For example, an agent's aggressiveness may change based on the number of squad members injured or killed.

HUMANITARIAN ASSISTANCE / DISASTER RELIEF OPERATIONS

This investigation of the use of agents for logistics operations was driven by an interest in an active study of HA/DR operations (Wolf 2003). There were two primary motivations. Foremost is the compelling fact that the Marine Corps can expect to be importuned as a first-responder to humanitarian crises in the future. The second impetus is that in HA/DR actions the primary role, and in fact accountability for success, is often apportioned to the combat service support community.

The Marine Corps and its Navy partner routinely operate in forward-deployed regions, uniquely positioning them to rapidly respond to pleas for help. These cries may be for immediate relief from the crippling effect of a natural disaster, as was the case when an earthquake struck the country of Turkey recently. They may be the swelling voices of citizens trapped in a man-made disaster brought on by civil conflict such as was the case most recently in Liberia. In either circumstance, the Marine Corps and the Navy are trained and outfitted to respond purposefully. The Marine Expeditionary Unit (MEU) deploys with a full compliment of equipment allowing it to provide immediate life-saving services and then transition to relief and sustainment operations.

In HA/DR environments one often sees services such as transportation, distribution, medical attention, and engineering efforts rise to the top of the priority list. Logisticians may find themselves in the unique position of being the main effort with infantry providing security for their missions. Furthermore, logisticians must be prepared to take the lead in drafting operational plans. The ability to quickly put together ABMs and explore their behavior over a wide range of parameter settings might help support logistics operations during a humanitarian crisis.

Most operators, logisticians, and analysts think of logistics support in terms of hard numbers such as the number of meals delivered, or the number of miles driven. However, logistical scenarios are exactly the type of loosely-defined problems which lend themselves well to abstract study using agents. For example, one can think of any number of decisions that could affect the success of a simple resupply mission in an urban HA/DR environment. Intangibles, such as foot traffic, road accessibility, harassment, and the necessary interaction between the military, non-governmental organizations, and the host nation can all have effects on the success of the operation.

We use MANA to model a convoy operating in an urban environment. Our scenario provides a framework for a more detailed discussion of agent characteristics, and also shows how a modeling platform can be used to quickly set up a basic scenario. (Other platforms also have graphical user interfaces to facilitate the scenario setup, though they all differ in the details of the modeling process.) Figure 1 depicts a screen capture during an execution of our ABM. The yellow entities are neutral agents, each representing a household of eight people requiring aid. These neutrals are divided into two squads, northern and southern. Initially, the northern neutrals begin making their way to the humanitarian assistance (HA) site closest to them, represented by the yellow flag in the center of the upper screen. Concurrently, southern neutrals move towards the southern HA site. Blue agents represent a convoy of Marines (or a relief agency) with a Marine security escort. The blue agents 'drive' across the top of the screen until they come to their first waypoint, represented by a blue flag. They make a left-hand turn and continue traveling south.

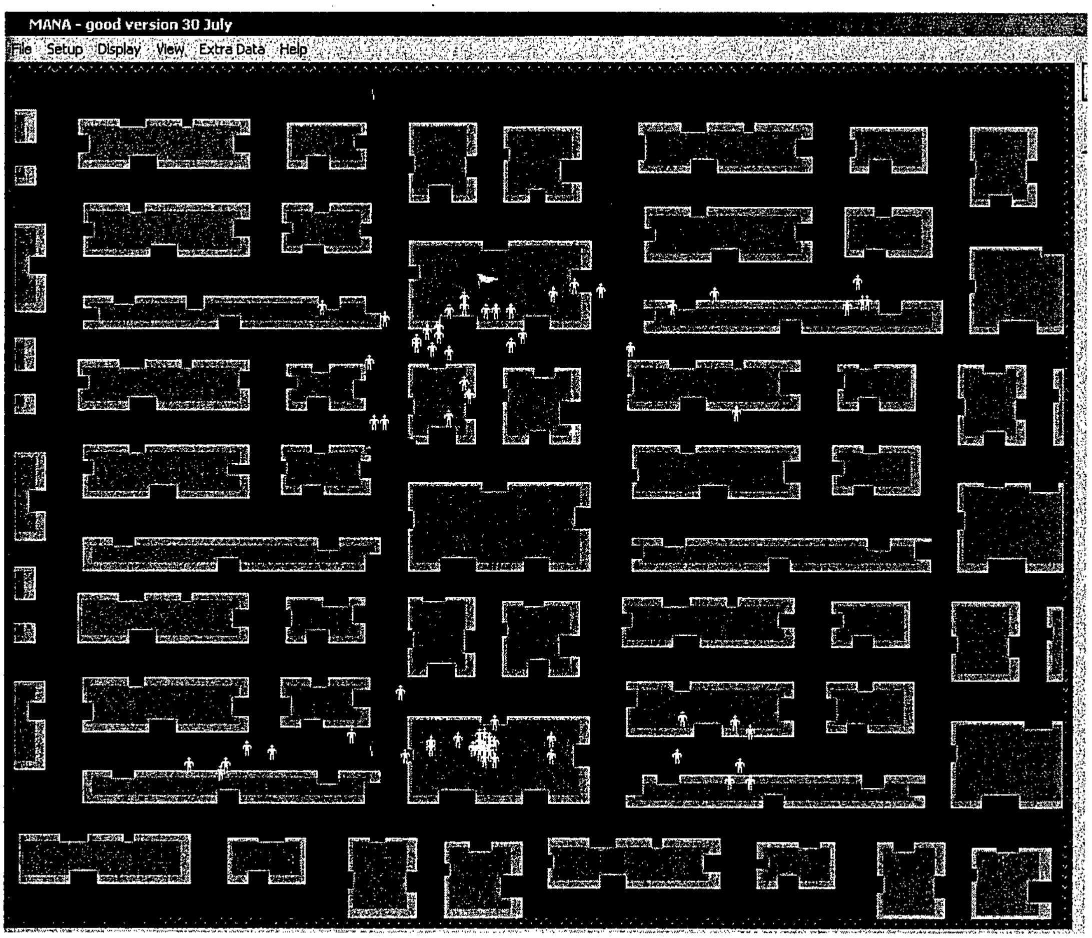

Figure 1. MANA Food Distribution Base-Case Depiction

As the northern neutrals sense the convoy passing by, they will speed up and try to follow the trucks. We included a lone red agent in our base-case scenario to introduce the possibility of random harassing fire as might be encountered in a civil war or other man-made humanitarian crisis. The red agent will take a shot and then try to run away. If the security element can identify the aggressor it will return fire, but the convoy's response will be to speed up and drive out of the area. The convoy will eventually make their way to the southern HA site and begin feeding the neutrals.

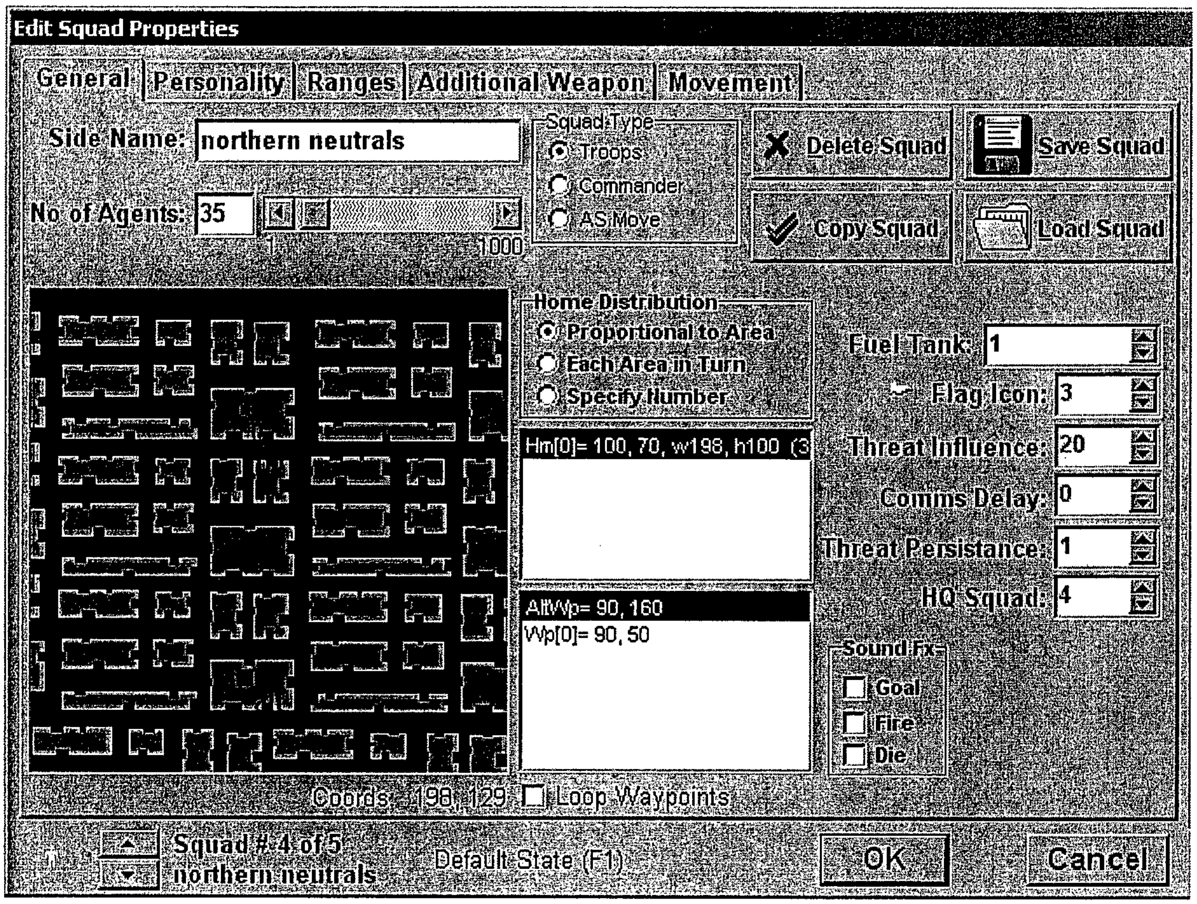

Figure 2: General Properties of a Squad of Agents in MANA

We now discuss in more detail how MANA incorporates the three aspects of agents—general, physical, and personality characteristics—into this scenario. In Figure 2, a squad of 35 agents (representing 35 households of eight people each) is classified as *northern neutrals*. We specify most of the general characteristics for these agents using this 'General' tab as well as the "Movement" tab. Their initial positions are randomly chosen throughout a user-specified region—in this case, the upper part of the screen. Additionally, we can specify their set of waypoints, threat size, threat rate, etc. The black terrain represents roads, which are easily trafficable. The gray areas depict walls or barriers impenetrable to sight and fire. These barriers surround green areas where movement is slower, representing the inside of buildings or courtyards. Thus, MANA has simple representations of terrain that remain constant through the simulation run. Other squads can be added, and each squad can be given distinct characteristics.

Figure 3 illustrates some of the physical characteristics within the MANA platform. In this screen, the analyst can specify the sensor and firing ranges for a particular squad, as well as the movement speed, survivability, stealth, firepower, and values representing its allegiance and those it considers a threat. The settings in Figure 3 are those for Squad #5—a lone aggressor who perceives the HA/DR convoy as a threat. The aggressor carries a weapon with limited firepower and can provide harassing fire from close range. In contrast, the northern neutrals in the HA/DR scenario were not supplied with weapons and perceive no other agents as threats.

In addition to their physical characteristics, each agent has a set of internal decision rules that guide its movement desires. This gives each agent a personality or behavioral characteristic. In MANA these personalities are translated into movement by the relative weights for desiring to move in certain directions. Figure 4 shows, e.g., that the agent has a strong desire to approach its enemy and a slight desire to stay near neutrals. These characteristics make sense for an aggressor.

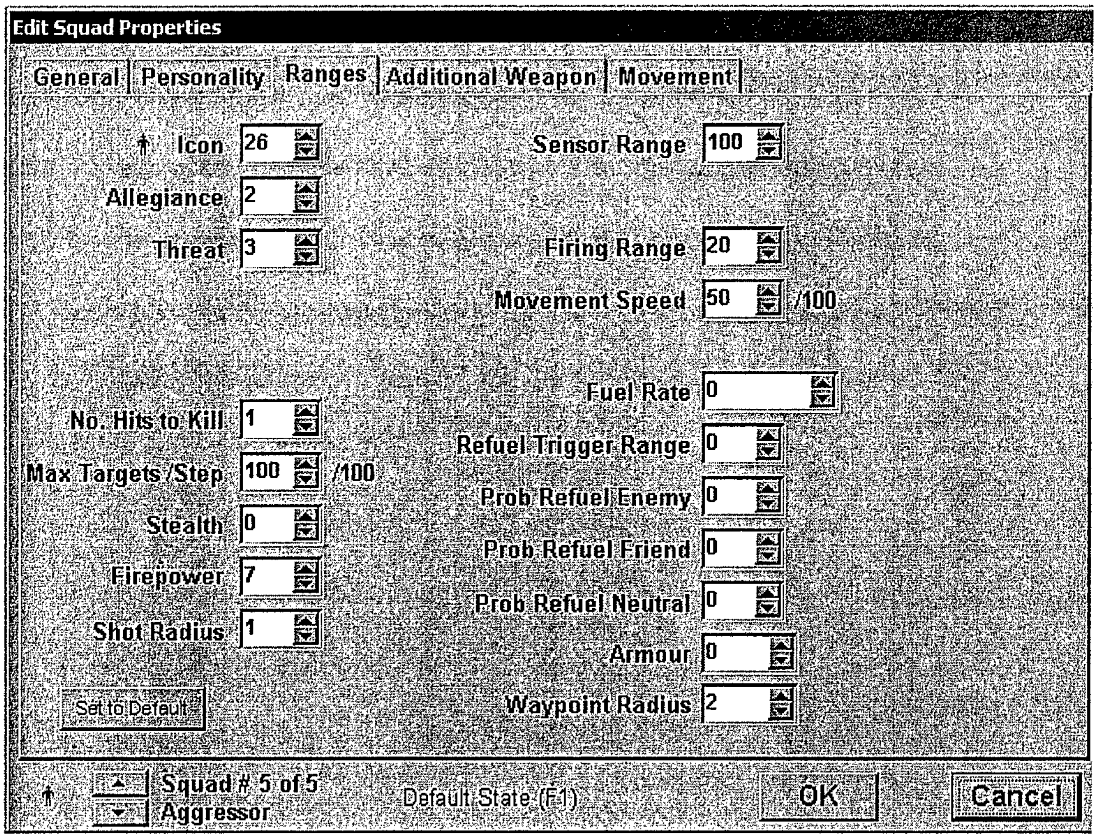

Figure 3. Aggressor Sensor, Movement and Firing Ranges

Another important aspect of many ABMs is the ability of an agent to adapt not just its movement, but its personality, based on its environment. The 'Trigger States' column at the right of Figure 4 lists the changes in the environment that can trigger a change in the agent's personality. If none of the trigger states are checked by the analyst, then the agent will follow the same set of rules throughout the simulation. In this case, after the agent takes a shot at the humanitarian assistance convey or its security element, it will enter the retreat state. At this time the aggressor's movement switches from a desire to engage its enemy to a desire to distance itself from the enemy threat and alive enemies. The retreating agent also prefers easy-going terrain that offers some cover and concealment. These new desires are implemented via the analyst specifying new personality weighting factors.

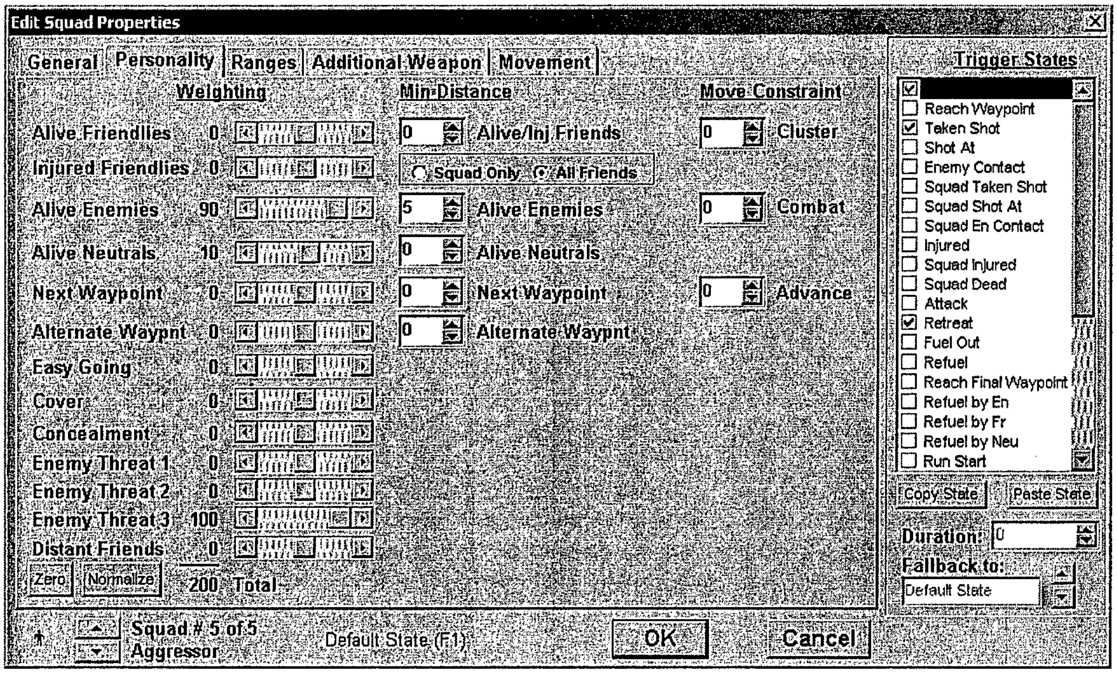

Figure 4: Aggressor Personality in the Default State

To summarize, agents are autonomous individuals or groups which possess general characteristics, physical characteristics, and internal rules that guide how they moves and react to their environment. Agents may also have the ability to change these rules over time.

REQUIRED ELEMENTS FOR EXAMINING LOGISTICS OPERATIONS VIA AGENT-BASED MODELS

While ABMs have been around for a number of years, those used in the military have been warfighting models. The agents possess weapons, abilities to sense, communicate, and move, and also can be given different sidednesses or allegiances. However, they do not have the abilities to carry, consume, or transfer resources. Note, this is not intended as a criticism of the current ABMs. One goal of the simple models used by Project Albert is to distill only the essence of the problem. These problems are designed to provide insights and directions, not numerical predictions. Nonetheless, logistics functions are extremely important for the U.S. Armed Forces. We now describe the characteristics that are essential if ABMs are to be used for logistics operations:

- Defining a commodity.
- Attaching a commodity to an agent.
- Transferring a commodity between agents.
- Defining appropriate measures of effectiveness (MOEs) for evaluating the effectiveness of logistics operations.

We believe these activities form the minimal core of capability.

Defining a Commodity

In the U.S. Marine Corps, *commodity* is a catch-all term for ammunition, fuel, food, equipment, etc. We believe that commodities should also be modeled as generic items in agent-based platforms. The user/analyst will define the commodities. These may also include notions of health and fatigue.

Two generic types of commodities are generally available: bulk items and individual items. Bulk items might include fuel, food, and ammunition. Individual items might include spare or replacement parts, or large pieces of equipment. Note that some commodities might be modeled as either bulk or individual items. For example, the 'health' of a squad might be improved *en masse* when a supply vehicle arrives at the site, or 'health' might be transferred on an individual basis, as in distributing individual meal rations or vaccines. Commodities may also show up as both bulk and individual items within the same simulation. For example, a fuel truck uses up fuel during the delivery process: for time-step models, but at the same time carries fuel in bulk to give away.

In addition, some sense of dimensionality is needed for a commodity. This should be user-defined, rather than built in, but it needs to make sense in the context of the problem. Bulk commodities (such as fuel in a fuel truck) can be carried in any fraction of the carrying agent's capacity. In contrast, individual items may have restrictions on the amount that can be carried. Dimension might be cubic feet, length, width, height, or short tons. The concern here, once again, is in modeling a notional idea of the dimensions and carrying capacities rather than a detailed description, so the critical dimension should be used. For example, a landing craft utility can carry two tanks (because of weight) or twelve high mobility multipurpose wheeled vehicles (because of size). The sense of dimension is particularly important when we are dealing with multiple commodities. If we are dealing with individual items, a truck might be able to carry four large items *or* 60 small items. Dimension should also ensure that, e.g., we cannot make the truck carry four large items *and* 60 small items (though it could carry two large items and 30 small items). Conversely, it would not make sense to carry half of a large item because this unit is not divisible further.

In practice, the shape of large items impacts how many can be packed into a single truck. Shape considerations might dictate that an agent carrying only half of the allowable number of large items might be able to utilize somewhat more (or somewhat less) than half of the small item capacity. Given the level of abstraction for other aspects of the ABMs, we do not feel this high level of detail is warranted.

Attaching a Commodity to an Agent

Agents must have a means of *carrying* a commodity. While one might think this capability is already in place in ABMs such as ISAAC and MANA (after all, agents can be given weapons), the weapons are an intrinsic part of the agent rather than something they might or might not be carrying. So, the appropriate dimensions (cubic feet, weight, length, etc.) that an agent can carry must be defined for that agent. Clearly, these can differ widely—any scenario involving logistics operations likely includes some agents (such as trucks, helicopters, ships) that can carry 'a lot' and others (such as individual Marines or civilians) that can carry 'a little.'

There is also a need to differentiate between an agent's own commodities and those it can give away. The agent's own resources should decrement—either regularly over time, or when used—but should have no effect on the resources the agent intends to give away. For example, a fuel truck will use up its fuel while traveling to its destination, but the fuel it is carrying will be unaffected during this travel. There also needs to be a mechanism to 'run out' of a commodity, which should in turn trigger new behavior.

Transferring Commodities

Transferring a commodity should cause a state change in the agent giving up the commodity. For example, once a truck has delivered its load, it may be able to move faster. Once it is empty, its propensity may be to return to the logistics base so it can pick up additional commodities—perhaps of a different type.

Commodity transfer should cause a state change in the receiving agent, as well. For example, this agent is now carrying more, and might move more slowly. Alternatively, if the transferring agent's commodity is notionally viewed as medicine or food, the receiving agent's notional commodity of *health* could increase.

Redistribution schemes also need to be considered since they will have an impact on how the scenario progresses. Consider a truck arriving to transfer ammunition. The truck could personally distribute individual items (ammunition packs) to individual Marines when they came in contact with one another. Alternatively, one might want to model the entire squad's ammunition being updated at once with a single transfer away from the truck. Between these two alternatives, there might be a distribution scheme where, e.g., the truck distributes ammunition to a small number of agents who then redistribute (most) of it to other agents in the squad. For modeling ease, it would be helpful to have simple check-off boxes for the analyst to indicate the appropriate distribution mechanism associated with particular agents and commodities.

Finally, we need to define transfer rates for each commodity. These should again be specified for both bulk and individual commodities. If transfer rates are given in units per time step, it makes sense that bulk transfer rates will tend to be longer than individual transfer rates.

Other refinements could be made. For example, in real-world logistics operations there may be a setup time associated with preparing for transfer, or transfer rates might not be constant. We do not feel these characteristics need to be added to ABMs. First, trying to model individual set-up times or accelerated transfer rates adds unnecessary detail relative to other model aspects. Instead, notional 'average' or 'typical' transfer rates can be specified by the user. If setup times might play an important part in the model (e.g., a squad waiting for ammunition might be fired upon and destroyed by the enemy), then trigger states could be used to have an agent wait a short time between arriving at the transfer location and beginning to transfer commodities. This is part of the balance between keeping the model simple and abstracting enough of the essence of the problem to gain insights.

Useful Measures of Effectiveness

An MOE is an objective, quantitative expression of performance appropriate to the context in which it is being used. Generally an MOE relates resources input to obtain a given measure of output. It must have real scales upon which to measure inputs and outputs. Schrady (1989) says, "MOEs in the affairs of man and society tend to be relative rather than absolute." Identifying appropriate MOEs in military logistics operations will often be controversial because of the political nature of the operations themselves. At the operational level or above we quickly get tied to political objectives that are neither easily defined nor readily measurable. So, level-of-effort measures at the task level or the mission level are used to support task-performance measures.

Even with this narrower scope, there is an art to choosing appropriate MOEs. For example, after a (natural or man-made) disaster there may be several measurable objectives for logisticians, such as the number of miles of road rebuilt and the number of bridges repaired. However, without information about the *priorities* of these objectives relative to other objectives it is difficult to quantify success. It may be that the benefit of building roads, while necessary for long-term redevelopment, pales in comparison with the need for producing and distributing potable water, for example. Similarly, measuring a overall order lead times and fill rates and lead times may be counterproductive if it means the MOE remains high even while the supply of mission-critical spare parts suffers because the capacity is being used to deliver routine, non-critical resources.

We also need to measure our objectives as *ratios* or ***rates*** relative to some established standard. For example, just as counting the number of enemy killed is only informative when we know the size of the enemy forces, counting the number of people fed is only informative when we know what percentage of the population requires food.

Some MOEs lack *comprehensiveness* or the ability to fully measure mission success. We may be required to implement several MOEs to completely assess how we are accomplishing the list of tasks. We want to ensure we are measuring the effectiveness of the effort as a whole and not just one aspect of the effort or our local piece of the relief mission. Reliance on a single MOE to account for a problem with many causes is inadequate. For example, in any joint or combined exercise a combination of measurements among the various agencies may better capture the totality of the operational effort.

Another complication often found in logistics operations is the importance of identifying *trends*, such as the rate of decline in the number of dysentery cases or the rate of increase in the number of households whose electrical power has been restored. Tracking trends may provide a much better indication of effectiveness than simply collecting aggregate outcomes at the end of an operation.

In short, there is an art to choosing an MOE that measures what we want to test in a way that does not assume away tangent factors. The MOEs for the Project Albert ABMs currently include things such as the number of agents killed or injured, or in some cases the time until a certain event. However, with the current suite of modeling platforms there is no capability for measuring other MOEs of direct interest to logisticians, such as stockage levels or transfer times.

HA/DR EXPERIMENT

We have already described the basic setup of our urban, HA/DR scenario in MANA. We chose that platform in part because MANA's fuel rate and refuel trigger range options (see Figure 3) were characteristics that appeared useful for modeling logistics operations. We initially hoped to model the food distributed by the convoy as 'fuel' and measure effectiveness by the amount of food provided to the neutrals. However, we found the fuel/refuel operations did not take place the way we anticipated. In MANA, the refuel state causes an agent to stop decrementing fuel while in that state and does not result in any fuel transfer. Once an agent leaves the refuel state it begins using fuel at the initial rate, and the fuel can go negative. There is effectively an unlimited fuel supply, so the fuel in MANA acts more like a counter than a commodity. Agents would expend less of a resource if, in fact, they were refueled at any point during the simulation than if they never received an influx. This is not useful for modeling the impact of timely logistics support.

Therefore, we end up *shooting* the neutrals with food and looking at the number 'killed'—clearly not the measure we would like to report, although it does give us a surrogate for the amount of food distributed. Our task-performance MOE for the HA/DR scenario: the ratio of neutrals 'killed' to the entire population. Admittedly, we chose this MOE in part because we were limited to the measurements provided by the software, but we still believe this is an appropriate measure. It relates to the overarching mission, not solely on the military task. This ratio is preferable to, say, the time to arrive at the food distribution site because it focuses on the effectiveness of a task rather than on accomplishing the task. It is simple to compute given that we know the population of the affected area and can count the number of people we serve, so collecting the information to assess one's effectiveness should not put an undue burden on those providing relief.

Having devised a creative way to model food distribution in MANA, we moved on with our overall goal to investigate whether or not ABMs could provide useful insights for planning logistics support operations. We made thousands of preliminary runs to make sure our understanding of the model's behavior was accurate. We identified 40 squad/state/parameter combinations to explore. Here the 'squad' was one of the five (northern neutrals, southern neutrals, convoy, convoy security, or aggressor) implemented in our model. The 'state' corresponded to one of the states defining the behaviors for that squad (e.g., the convoy could be in the 'default,' 'shot at' or 'arrived at final waypoint' state). The 'parameter' represented a factor dealing with sensor range, communications delay, movement speed or precision, etc., that we could test at various numerical settings. We then used an efficient experimental design that allowed us to examine the impact of simultaneously changing the specified values of these 40 squad/state/parameter combinations (the associated set of values is called a design point). Similar designs have been successfully used for other Project Albert investigations (Lucas et al. 2002-3, Sanchez and Lucas 2002, Kleijnen et al. 2003). Our final experiment (with 50 replications at each of 640 design points) required 32,000 simulation runs, but even this large number of runs was completed in 7.5 hours on the Gilgamesh supercomputing cluster at MITRE.

Before running the experiment, we had hoped to find settings for factors Marines could control (such as movement speed, actions on contact, cohesion) that would work well across a wide variety of settings for neutral and aggressor squad factors. Unfortunately, it turned out that the Marines-only model could explain a mere 6% of the variation in the number of neutrals fed ($R^2 = .06$). By including the neutrals' sensor range in the model (i.e., assuming that the convoy can 'broadcast' its intention to distribute food at the southern HA site), the explanatory power improved substantially ($R^2 = .37$). We also considered models that only included factors having to do with neutrals receiving or sending information, and found a model with only 7 terms (4 main effects, 2 interactions and 1 quadratic effect) could explain nearly half the variation ($R^2 = .45$).

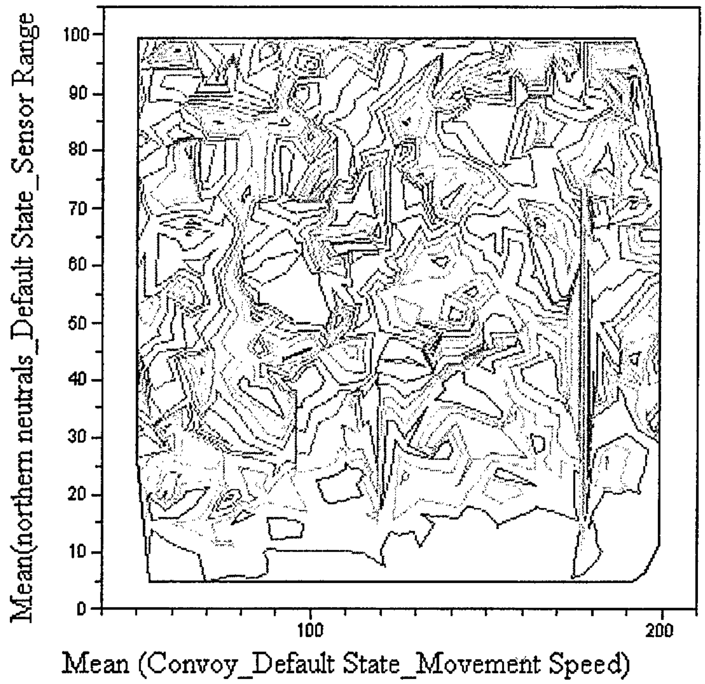

Figure 6: Contour Plot of Northern Neutral Sensor Range vs. Convoy Movement Speed

Contour plots provided further information about the relationships in the presence of interaction. For example, Figure 6 shows the result of crossing the northern neutral's default *sensor range* with convoy default *movement speed.* It appears when *sensor range* is below about 30 it does not matter how fast the trucks travel. In all cases, the fewest number of neutrals are fed at these settings. A sensor range of 30 translates into about two city blocks in MANA. As neutrals move around the scenario, most of the time they are either inside of buildings or moving between buildings. We suspect, in order for contact to be made with the convoy before the neutrals miss the opportunity to gain initial contact, they must detect the convoy further off. Otherwise their meeting with the convoy becomes merely chance. This explanation may be useful when planning operations in the presence of a highly mobile population. This is but one example of the specific findings (see Wolf 2003 for further details).

Through fitting our various models, we uncovered five critical points. First, we found the complex environment we had modeled could be effectively described by very few squad/state/factor combinations. Secondly, those combinations having to do with local communications proved to be vitally important. Third, interactions between these parameters provided additional explanatory power. Next, actions of the lone red agent had negligible impact. Finally, we found it was imperative for the relief agency to gather and use information from the local population.

Based on the results of our experiment we have two general recommendations. First, we strongly encourage analysts to try fitting very large sample spaces. We found even when we began by trying to measure virtually every interaction our screening technique quickly identified the heart of the problem, but at the onset of the experiment we did not know which factors would emerge as the most important determinants of success. We recommend researchers adopt this type of procedure to study highly complex scenarios. One note of caution is in order. Agent-based simulations are highly abstracted and may require creative manipulation and interpretation of the parameters and MOE when designing the simulation. The analyst must take a hands-on approach in both the scenario development and the analysis loop in order to assess whether or not the appropriate factors have been considered and that the results are not simply artifacts of the modeling platform.

Second, when operating in an urban HA/DR environment, the response the relief agency is trying to illicit from the local population must be considered. Relieving agencies must not rely solely on the parameters they have control over, but should also allocate intelligence assets to the task of deciphering local communications. If their relief plan requires the local population to respond to some action they are taking, they must determine how they will communicate this to the local inhabitants. In our case, the northern neutrals needed to recognize the convoy, understand the convoy would not stop at the northern HA site, and decide to follow the convoy to the southern site. To encourage these things to happen the convoy should broadcast its route plan and distribution scheme, and generally facilitate communications between locals.

We caution that these findings apply to the scenario we developed and may not apply in a different environment. Because our aggressor was relatively timid, that is, he only fired once and then ran away; the chances of impacting the success of the mission were very low. We recommend that relieving agencies thoroughly understand the nature of the threat they face. If that threat follows our pattern, a security element and lightly sandbagged vehicles are sufficient. They need not employ assets such as armored vehicles to predict success.

OTHER CREATIVE MODELING APPROACHES

Although the ABMs we explored did not include the ability to directly model logistics functions when this study was conducted, we saw several creative work-arounds adopted. We now present two different operations—modeling supply shortages and modeling supply fills—on ABM platforms other than MANA in order to illustrate that there is not a single, unique modeling approach. In fact, it can be very beneficial to attempt to address similar questions using different modeling platforms (which, in turn, make use of different internal logic and assumptions) to verify that results obtained from one implementation are not simply an artifact of the modeling platform.

The first modeling topic we discuss is that of implementing supply shortages in Pythagoras. Recall that our MANA HA/DR scenario had agents of three allegiances: blue, red, and yellow. In fact, while the colors of the agents as they appear on the screen may be arbitrarily specified by the user, each agent perceives only three sides: friendly, enemy, and neutral. These are determined by the 'headquarters' associated with the squads. For example, in our MANA scenario the northern and southern neutrals and the red agent all had the same headquarters.

In contrast, Pythagoras (Northrop Grumman 2003) models affiliation in a different manner. Each agent has a color that corresponds to the amount of red (0-255), green (0-255) and blue (0-255) in its composition, for a total of over 16 million possible colors. While the human eye cannot distinguish among this many colors on the screen, these codings allow fine gradations in how agents perceive and interact with one another. Each agent can use the amount of one of these three colors to define its friends (e.g., an agent whose blue level differs from mine by at most 40 is my friend) and the same color *or another color* to specify its enemies (e.g., an agent whose red level differs from mine by more than 5 is my enemy). An individual agent can be injured, killed, or have its color change within a simulation run as the scenario evolves. For example, Pythagoras has been used to model mob behavior where an agitator attempts to incite the crowd by bombarding it with small amounts of red, while the attempts of peace-keeping forces to quell the crowd are modeled by 'shooting' the civilian agents with weapons that reduce their red values.

For logistics operations, we found that with careful planning these hues can be used to model situations where supply shortages exist and transfers must be made. Figure 5 shows a graphical illustration of a simple situation involving three forward deployed units (squads of Marines). These have fixed positions, and are initially blue. Red agents (also fixed in location) act as commodity sponges: they decide to 'shoot' at agents with little or no red. Each time they fire at an agent they do not injure it, but change its color to increase the amount of red.

Systematic fire indicates a routine activity (such as the consumption of daily food rations) while random fire models the depletion of resources in an irregular manner, such as the use of ammunition during combat and non-combat situations. Eventually the Marines have sufficient red levels that they are no longer considered enemies of the red sponges. This corresponds to running completely out of a resource; in the absence of interaction with agents other than the red sponges, the forward-deployed units' color will remain constant from this point on.

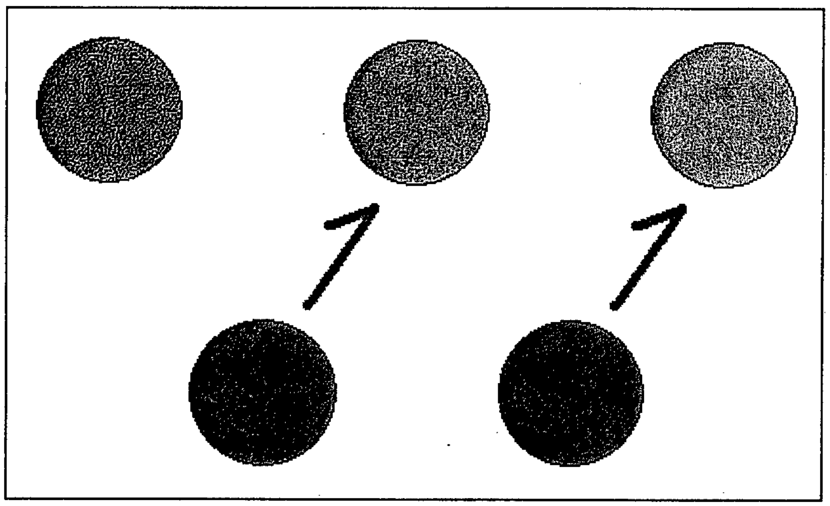

Figure 5: Use of Color to Depict Resource Levels in Pythagoras

Conceptually this took some thought. If the forward agents' commodity is ammunition, each 'shot' Red makes corresponds to rounds fired (and hence no longer available) by one of the forward-deployed squads. Similar logic, making use of more colors, can trigger resupply operations as the now-purple agents are perceived as enemies and fired on by a blue resupply agent to remove all red. However, the sensor ranges for the agents needed to be carefully chosen so that the blue base agent would not be perceived as an enemy and fired on by the red sponges, and the red sponges would not be fired on (and resupplied) by the blue base. So, while

Pythagoras may be a reasonable modeling platform for some logistics scenarios, the difficulties involved in combining commodity usage with agent movement—an important aspect of our scenario—made it unsuitable at the time for our HA/DR scenario.

We also considered the Socrates model (L-3 Communications Analytics Corporation 2003) for modeling supply fills. One feature of Socrates that made it attractive for modeling logistics operations was the ability to prioritize fills by giving agents different profiles. This is in consonance with current Marine Corps operations, where requests are prioritized on the basis of the requesting unit's deployment status, the type of commodity, and the pattern of demand. For example, a forward-deployed MEU has greater priority than a training unit; delivering a replacement tank engine has greater priority than delivering a replacement sling for an M-16, and scheduled deliveries of items with frequent, routine, relatively constant demand may be (but may not be) overridden if there is demand for an unusual or expensive item.

In Socrates, an agent attempts to shoot the most urgent 'threat' or 'target' (in logistics terms, resupply the most urgent request) within its firing range when it has a chance to fire. Requesting agents can be given different colors according to their priority levels, and different speeds which lead to varied windows of time in which their request can be filled. Figure 6 depicts this by showing a sequence of snapshots of orders arriving for fill. In the first frame, the blue logistics agent chooses to resupply one of the low-priority (green) orders. In the second frame, the blue agent becomes aware of middle and high priority orders (yellow and red, respectively), and chooses to fill the high priority item. In the third frame, one high and one low priority request have been satisfied. The time has expired for filling the middle priority order (i.e., its speed has already taken it out of range) so the blue logistics agent fills another low-priority request.

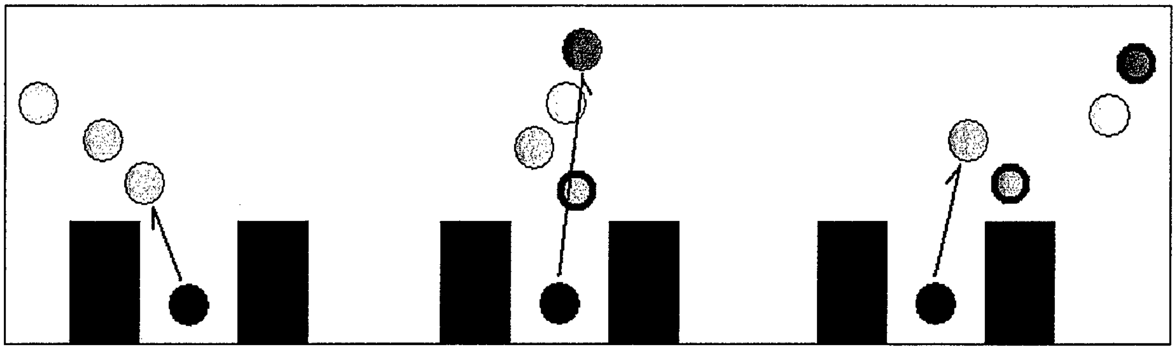

Figure 6: Modeling Supply Fills in Socrates

Nonetheless, we chose not to use Socrates as the platform for our HA/DR scenario. While the ability to prioritize resupply requests (via treating them as different levels of threat) was interesting, we were not interested in utilizing this for food distribution in our HA/DR operations. Also, any type of complicated terrain coupled with agent movements induced a series of calculations within the program that quickly overloaded the model, causing it to shut down. Terrain was a key aspect of our urban scenario.

In short, while the available suite of agent-based platforms did not make it easy to model logistics operations, it was still possible to examine some aspects. Calling attention to this limitation in Project Albert's suite of ABM platforms has already had an impact. We believe we helped to "get the ball rolling" by identifying, in the early stages of our simulation setup, the need to model logistics explicitly. Capt. Wolf was privileged to work with the developers of Socrates at a logistics workshop in December 2002. The need to be able to explicitly model the retention, transfer, and consumption of resources was identified to the developers during this workshop. They have quickly updated the program to include these functions. The authors, along with other Project Albert collaborators and developers from Socrates and Pythagoras, constructed a prototype seabasing scenario at a recent workshop (7th Project Albert International Workshop, Woodbridge, VA, 7-26 September 2003). MANA has modified its fuel/refuel characteristics in a subsequent release (Anderson et al. 2003). It is now possible to include refueling activities in a scenario, though not without careful modeling to coordinate negative fuel usage rates for the agent supplying resources and positive fuel usage rates for the receiving agents.) We have also discussed the needs for a broader set of MOEs with the Project Albert community and software developers.

CONCLUSIONS

Philosophically, we believe that there can be great utility in using agent-based models (ABMs) as a means of exploring highly complex scenarios. ABMs easily allow the researcher to develop and test a complex scenario. By inculcating autonomous agents with simple desires and letting them individually make local decisions, an almost endless number of global outcomes are possible from a simple abstraction of a complex problem. The speed with which these simulations can be created is of course, offset by the level of abstraction and this must be considered before accepting the validity of the effort. We have found the ability to abstractly model complex human interactions is well worth what we may sacrifice in terms of the detail in the simulation.

Logistics support plays a primary role in humanitarian any military operation, and the ability to mimic the vagaries of human behavior may provide better insights for those planning these operations. However, in order to be more useful in such situations, ABMs must allow the analyst the capability of easily (1) defining generic commodities, (2) attaching commodities to agents, (3) explicitly measuring the transfer and use of these commodities, and (4) capturing appropriate information from the simulation runs to construct relevant measures of effectiveness.

At the present time, many deficiencies of current ABMs can be overcome with creativity, but this is a poor substitute for the ability to directly measure relevant aspects.

The way that data are generated from ABMs is also a key to providing useful insights and information to decision-makers. Our sample scenario showed that even though logistics operations can be replete with variables, mission success may dependent on only a handful of these factors and their interactions. Without the use of data farming it is quite likely that important factors—and interactions—will not be identified. Coupling intelligent data collection plans with the speed of data farming has a dramatic effect on the number of factors that can be explored simultaneously. The speed at which ABMs can be developed and run, coupled with data farming, means that analysts can explore interesting areas with quick turnarounds. Data farming, coupled with an intelligent design of experiments, gives the researcher the ability to screen for relevant factors over a very large design space. Complex problems—those including many variables and/or complex interactions—have the possibility of providing the greatest insights into logistics operations. In order to correctly identify the factors that are important contributors to mission success, analysts need a tool which is not limited to looking at, for example, five factors at four levels and their interactions. Our experiment considered 40 factor combinations at 640 different design points. This degree of complexity was not reasonable to explore a few years ago. To our knowledge, the highest number of factors and levels explored in an ABM up to this point has been 22 variables at 129 design points.

Additional research should be carried out using agents to model logistics support operations. Our study focused on food distribution but we can easily envision analyses being conducted on a variety of scenarios. Possibilities categorized as humanitarian assistance and disaster relief operations include studies of various temporary housing options, the migrations of displaced persons, the spread of communicable diseases as a result of poor conditions brought on by a disaster, or changes in the health of persons affected by disaster. Other logistics support operations abound, such as an ABM of seabasing operations to provide forward logistics support.

We were gratified to see our work was partly responsible for instigating the addition of resource capabilities in several agent-based modeling environments. We encourage analysts to begin exploring these capabilities. In the longer term, we envision a suite of logistics models comparable to the set of *urban* models and *weapons effects* models that currently exist for some of the software packages.

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LIST OF ACRONYMS

ABM	Agent-based Model
HA	Humanitarian Assistance
HA/DR	Humanitarian Assistance / Disaster Relief
MEU	Marine Expeditionary Unit
MOE	Measure of Effectiveness

DESCRIPTORS

Agent-based models

Logistics

Humanitarian assistance

Convoy operations

Project Albert